5 Decision Trees & Random Forest : Predict loan approval using a banking dataset

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import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
, accuracy_score
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns

#1 Load the dataset
#Example : Assuming 'loan_data.csv' where 'Loan_Status' is
 the target (Y= Approved, N= Not Approved)
 df = pd.read_csv('loan_data.csv')

# Preview the dataset
 print("Dataset Preview :")
 print(df.head())

#2. Handle missing values (simple fill or drop)
  df = df.dropna() # or you can use df.fillna(method='ffill')
                      depending on your data

#3. Encode categorical variables
#identify categorical columns
cat_cols = df.select_dtypes(include='object').columns
```

```
#label Encoding
le = LabelEncoder()
for col in cat_cols:
    df[col] = le.fit_transform(df[col])

#4. Prepare features and labels
X = df.drop('Loan_status', axis=1) #Features
y = df['Loan_Status'] # Target (1 = Approved, 0=Not Approved
                        after encoding)

#5 Split the data
 X_train, X_test, y_train, y_test = train_test_split(X, y,
 test_size = 0.3, random_state = 42)

#6 Decision Tree Model
 dtree = DecisionTreeClassifier(random_state = 42)
 dtree.fit(X_train, y_train)

#7 Random Forest Model
rforest = RandomForestClassifier(n_estimators = 100, random_state =
42)
rforest.fit(X_train, y_train)

#8. Predictions
 dtree_preds = dtree.predict(x_test)
 rforest_preds = rforest.predict(X_test)
```

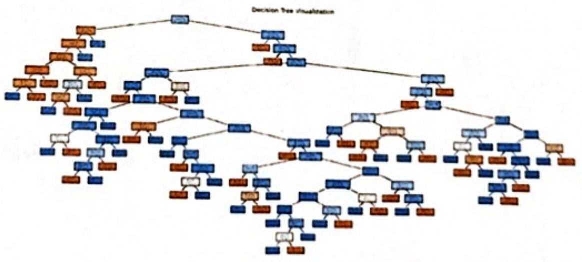
```
#9 Evaluation
print ("\n-- Decision Tree Performance ---")
print ("Confusion Matrix :\n", confusion_matrix(y_test, dtree_preds))
print(" classification Report :\n", classification_report(y_test, dtree_preds))
print ("Accuracy Score:", accuracy_score(y_test, dtree_preds))
print (" \n -- Random Forest Performance --- ")
print ("Confusion Matrix :\n", confusion_matrix (y_test, rforest_preds))
print ("classification Report :\n", classification_report(y_test, rforest_preds))
print ("Accuracy Score", accuracy_score (y_test, rforest_preds))

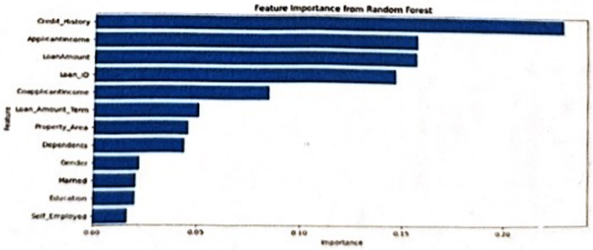
#10 Visulization of Decision Tree
 plt. figure(figsize =(20,10))
 plot_tree(dtree, feature_names= X.columns, class_names= ['Not Approved', 'Approved'], filled = True)
 plt.title('Decision Tree visualization')
 plt.show()

#11. Feature Importance (Random Forest)
 importances = rforest.feature_importances_ features = X.columns
 feature_importance_df = pd.DataFrame({'Feature': features, 'Importance': importances})
```

```
feature_importance_df
 feature_importance_df.sort_values(by='Importance', ascending=
 False)

plt.figure(figsize=(12,6))
ns.barplot(x='Importance'; data=feature_importance_df)
lt.title('Feature Importance from Random Forest')
lt.show()
```





5th prg output

```
Dataset Preview:
   Loan_ID Gender Married Dependents    Education Self_Employed \
0 LP001002  Male     No        0     Graduate          No
1 LP001003  Male    Yes        1     Graduate          No
2 LP001005  Male    Yes        0     Graduate         Yes
3 LP001006  Male    Yes        0 Not Graduate          No
4 LP001008  Male     No        0     Graduate          No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term \
0            5849                0.0        NaN             360.0
1            4583             1508.0      128.0             360.0
2            3000                0.0       66.0             360.0
3            2583             2358.0      120.0             360.0
4            6000                0.0      141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y

--- Decision Tree Performance --- Confusion
Matrix:
 [[21 23]
 [15 85]]
Classification Report:
           precision    recall  f1-score   support

0       0.58      0.48      0.53        44
1       0.79      0.85      0.82       100

  accuracy                         0.74       144   macro
avg       0.69      0.66      0.67       144
weighted avg       0.72      0.74      0.73       144

Accuracy Score: 0.7361111111111112

--- Random Forest Performance --- Confusion
Matrix:
[[19 25]
[ 3 97]]
Classification Report:
           precision    recall  f1-score   support

0       0.86      0.43      0.58        44
1       0.80      0.97      0.87       100

  accuracy                         0.81       144   macro
avg       0.83      0.70      0.72       144
weighted avg       0.82      0.81      0.78       144

Accuracy Score: 0.8055555555555556
```